Cambridge Journal of Regions, Economy and Society 2011, **4,** 221–235
doi:10.1093/cjres/rsr004
Advance Access publication 21 March 2011

Climate sensitivity of Indian agriculture: do spatial effects matter?

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Received on May 29, 2010; accepted on January 13, 2011

The paper contributes to current knowledge of climate change impacts on Indian agriculture by accounting for spatial features that may influence the climate sensitivity of agriculture. Using panel data over a 20-year period and on 271 districts, this study estimates the impact of climate change on farm level net revenue in India. The key findings reveal that there is a significant positive spatial autocorrelation and that accounting for this can improve the accuracy of climate impact studies. Furthermore, the paper argues that better dissemination of knowledge among farmers through both market forces and local leadership will help popularize effective adaptation strategies to address climate change impacts.

Keywords: climate change, Indian agriculture, environmental valuation, spatial panel data analysis, adaptation
JEL Classifications: Q1, Q54, R1

Introduction

Over the past two decades, the debate on global climate change has moved from scientific circles to policy circles with nation-states more serious now than before in exploring a range of response strategies to deal with this complex phenomenon. The Intergovernmental Panel on Climate Change (IPCC) in its fourth assessment report observed that, ''the warming of the climate system is now unequivocal'' (Solomon et al., 2007). Policy responses to climate change include mitigation of greenhouse gases (GHGs) that contribute to the expected changes in the earth's climate and adaptation to the potential impacts caused by the changing climate. Though GHG mitigation policies have dominated overall climate policy so far, adaptation strategies are now coming to the fore in order to formulate a more comprehensive policy response to climate change.

One of the crucial inputs needed for policy formulation on mitigation and adaptation is information on the potential impacts of climate change on various climate-sensitive sectors. Impacts on agriculture due to climate change have received considerable attention in India as they are closely linked to the food security and poverty status of a majority of the population. The studies have used two basic methods to estimate the economic impact of climate change on agriculture[1]: (i) an agronomic–economic approach (also referred to as the crop modeling approach and the production function approach) that focuses on the structural modelling of crop and farmer responses, combining the agronomic response of plants with the economic/management decisions of farmers. Among the studies that have followed this approach are Rosenzweig and Parry (1994) and Kumar and Parikh (2001a); (ii) a spatial analogue approach (referred as the Ricardian approach) that exploits observed differences in agricultural production and climate among different regions to estimate a climate response function. Among the studies that have used this approach are Mendelsohn et al. (1994), Kumar and Parikh (2001b), Seo et al. (2005) and Sanghi and Mendelsohn (2008).

The Ricardian approach has received widespread attention and criticism due to its elegance and the strong assumptions it makes. Several studies in India have followed this approach in the past to assess the climate sensitivity of Indian agriculture (Kumar and Parikh, 2001b; Mendelsohn et al., 2001; Sanghi and Mendelsohn, 2008). This paper contributes to existing knowledge on this field in India by addressing the importance of accounting for spatial features in the assessment of climate sensitivity. In conventional Ricardian studies, the units of analysis (say, districts) are implicitly assumed to be perfectly substitutable across space. However, in reality, the values of variables (such as crop output and inputs) in districts are defined not only by local conditions but also by the conditions in the neighbouring districts. This is what we refer to in this study as spatial autocorrelation of the dependent variable. Alternatively, the spatial distribution of agricultural land within and across districts could affect the error term structure. Ignoring the spatial correlation of error terms can lead to an under-estimation of the true variance–covariance matrix and hence to an over-estimation of the *t*-statistic. We refer to it in this study as the spatial autocorrelation of error terms. The study specifically assesses the evidence for spatial autocorrelation of variables (and errors) and attempts to correct for the same. The paper uses spatial panel data analysis in order to estimate the climate response function under various spatial econometric specifications and uses the estimated climate coefficients to predict the impacts due to climate change on Indian agriculture.

The rest of the paper adopts the following structure: the next section provides a brief review of the literature on the Ricardian approach and climate change impact studies on Indian agriculture. The third section explains the model structure and data used. The fourth section presents results and discusses the distributional issues of climate change impacts on Indian agriculture. The last section discusses the policy implications of the findings of this research.

Climate change and agriculture

Climate change projections for India for the 2050s suggest an increase in temperature of 2–4°C for the region south of 25°N and by more than 4°C for the northern region. While there is likely to be little change in the average amount of monsoon rainfall, climatologists expect the number of rainfall days to decrease over a major part of the country. The expected changes in climate, especially rainfall, are also marked by significant regional variation, with the western and central parts witnessing a greater decrease in rainfall days compared to the other parts of the country. Climatologists have also projected an increase in the intensity and frequency of extreme events such as droughts, floods and cyclones (NATCOM, 2004).

Mall et al. (2006) provide an excellent review of the climate change impact studies on Indian agriculture mainly from a physical impacts point of view. The available evidence shows a significant drop in the yields of important cereal crops like rice and wheat under the changed climate conditions. However, Mall et al. (2006) indicate that the studies on the biophysical impacts on some important crops like sugarcane, cotton and sunflower are not adequate.

As mentioned above, the economic impacts of climate change are assessed either through the agronomic–economic approach or through the Ricardian approach. The first approach introduces the physical impacts (in the form of yield changes and/or area changes estimated through crop simulation models) into an economic model exogenously. In the Indian context, Kumar and Parikh (2001a) have estimated the macro level impacts of climate change using such an approach. They show that under doubled carbon dioxide concentration levels in the latter half of the 21st century, the gross domestic product would decline by 1.4–3 percentage points under various climate change scenarios, with adverse poverty effects. While this approach can account for the so-called carbon fertilization effects,[2] one of the major limitations is its treatment of adaptation. Since the physical impacts of agriculture are to be re-estimated under each adaptation strategy, the researchers can analyze only a limited number of strategies. It must be noted, however, that this approach can easily incorporate other adaptation strategies that are triggered by market signals.

In the Ricardian approach, Mendelsohn et al. (1994) have attempted to link land values to climate through reduced-form econometric models using cross-sectional evidence. Since this approach is based on the observed evidence of farmer behaviour, it could *in principle* include all adaptation possibilities. In fact, this approach treats farmers as though they have 'perfect foresight' and hence are better placed to implement all adaptation options. One of the main concerns of this approach is that it may confound climate with other unobserved factors. Further, the constant relative prices assumption used in this approach could bias the estimates (see Cline, 1996; Darwin, 1999; Quiggin and Horowitz, 1999 for a critique of this approach).

In the case of India, Kumar and Parikh (2001b) have used a variant of the Ricardian approach and showed that a 2°C temperature rise and a 7% increase in rainfall would lead to nearly 8.4% loss in farm level net revenue. The regional differences are significant with northern and central Indian districts along with the coastal districts bearing a relatively large impact. More recently, Sanghi and Mendelsohn (2008) also estimated similar impacts due to climate change on Indian agriculture. As crops are more sensitive to temperature changes (Lobell and Burke, 2008), in all these studies the large negative effects of temperature increase outweigh slight positive effects due to rainfall increase.

The Ricardian model specification assumes that all heterogeneity across cross-sectional units is controlled for by the observed explanatory variables including the climate variables. Thus, it is very important that the model specification is accurate so that climate coefficients capture only the influence of climate. Further, since there is scope for learning across spatial units through communication and information diffusion, it is important to account for spatial correlation in the Ricardian analysis using cross-sectional data. It is this latter issue that the present study focuses on. Depending on how the spatial correlation would enter into the Ricardian analysis using cross-sectional data, some recent studies assessing climate change impacts on agriculture in the USA have either assumed that the dependent variable is spatially lagged (Polsky, 2004) or the error term is spatially correlated (Schlenker et al., 2006). Either way, these studies have argued for the need to account for spatial correlation in the Ricardian analysis. The present study aims to bridge the knowledge gap in the Indian context by attempting to get accurate estimates on the climate sensitivity of Indian agriculture through specifically accounting for spatial correlation of the cross-sectional units in the Ricardian analysis.

Model specification and data

While the original Ricardian approach developed by Mendelsohn et al. (1994) estimated the relationship between land values and climate due to nonexistent and/or absence of well-functioning land markets in the developing countries, a variant of Ricardian approach has been used in the earlier Indian studies (see Kumar and Parikh, 2001b; Sanghi and Mendelsohn, 2008). In place of land values, farm level net revenue is used as a welfare indicator and the value of the change in the environment is assessed through change in farm level net revenue. The Ricardian model is thus specified as follows:

$$\begin{aligned}\mathrm{NR} = f(&T_j,\ T_j^2,\ R_j,\ R_j^2,\ T_jR_j,\ \mathrm{SOIL},\ \mathrm{BULLOCK},\\ &\mathrm{TRACTOR},\ \mathrm{POPDEN},\ \mathrm{LITPROP},\ \mathrm{CULTIV},\\ &\mathrm{IRR},\ \mathrm{ALT}),\end{aligned} \tag{1}$$

where, NR represents farm level net revenue per hectare in constant rupees and T and R represent temperature and rainfall, respectively. It is noteworthy that based on the existing literature, we adopt a quadratic functional specification along with climate interaction terms (see Kumar and Parikh, 2001b; Mendelsohn et al., 1994, 2001; Polsky, 2004; Sanghi and Mendelsohn, 2008; Schlenker et al., 2006; Seo et al., 2005). The control variables include soil (SOIL, captured through dummies representing 19 soil types[3] and five top-soil depth classes), the extent of mechanization (captured through the number of bullocks and tractors per hectare; BULLOCK, TRACTOR), the percentage of literate population (LITPROP), population density (POPDEN), altitude (ALT, to account for solar radiation received), the number of cultivators (CULTIV, to serve as proxy for household/non-hired labour[4]), the fraction of area under irrigation (IRR). We do not include the output prices in the model. This is because an earlier study by Kumar and Parikh (2001b) has shown that the climate coefficients have not significantly changed when the prices of major cereal crops are included in the model specification.

We use pooled cross-sectional and time-series data to estimate the above model. Districts are the lowest administrative unit at which reliable agricultural data are available. We use a comprehensive district level data set for the period 1966–1986 for the purpose of the analysis.[5] The data set covers districts defined according to the 1961 census across 13 major states of India (Andhra Pradesh, Haryana, Madhya Pradesh, Maharashtra, Karnataka, Punjab, Tamil Nadu, Uttar Pradesh, Bihar, Gujarat, Rajasthan, Orissa and West Bengal). The data set includes 271 districts in all.

The variables covered in the data set include the gross and net cropped area, the gross and net irrigated area, the cultivators, the agricultural labourers, the cropped area under high-yielding variety seeds, the total cropped area under five major crops (rice, wheat, maize, *bajra* and *jowar*) and 15 minor crops (barley, gram, *ragi*, *tur*, potato, ground nut, tobacco, *sesamum*, *ramseed*, sugarcane, cotton, other pulses, jute, soybean, and sunflower); bullocks, tractors, literacy rate, population density, fertilizer consumption (N, P, K) and prices, agricultural wages, crop produce, farm harvest prices, soil texture and top soil depth. For purposes of analysis, we define farm level net revenue per hectare as follows:

$$\text{Net Revenue per ha} = \frac{((\text{Gross Revenue}) - (\text{Fertilizer and Labour Costs}))}{\text{Total Area}}, \tag{2}$$

where gross revenue and the total area are over the 20 crops mentioned above, the fertilizer costs are the total yearly costs incurred towards the use of fertilizer for all the crops and the labour costs are the yearly expenses towards hiring agricultural labour. We do not include costs attributable to cultivators, irrigation, bullocks and tractors in the net revenue calculations because appropriate prices are difficult to identify. However, we use these variables as control variables in the model as specified in (1). It is possible that some of these control variables are endogenous in nature and hence do not strictly qualify as exogenous variables. We have included them as exogenous variables in line with the existing literature on climate change impacts (Kumar and Parikh, 2001b; Sanghi and Mendelsohn, 2008).

Unfortunately, there is no ‘clean’ climate data available for the analysis. Meteorological data are collected at the meteorological stations and any district may have one or many stations within its boundary. Since all other data are attributable to a hypothetical centre of the district, it is necessary to work out the climate data too at the centre of the district. For this purpose, it is customary to interpolate meteorological station data to arrive at a district specific climate (see Kumar and Parikh, 2001b for more details on the surface interpolation employed to generate district level climate data). We use climate data corresponding to about 391 meteorological stations spread across India for the purpose of developing the district level climate. The data on climate—at the meteorological stations and hence at the districts—correspond to the average observed weather over the period 1951–1980 as documented in a publication of the India Meteorological Department. We represent all the climate variables through 4 months, January, April, July and October, corresponding to the four seasons. The climate variables include average daily temperature and monthly total rainfall in these 4 months.

We measure the dependent variable (namely, net revenue) in (1) and some of the explanatory variables (such as population density, tractors, bullocks, etc.) for every single year of the entire time period. If annual weather data for each district were available for a continuous period of time, then we could have used the rolling averages of 30 year weather data as 'climate' for each year. That is, for the year 1966, the average weather over the period 1937–1966 would serve as climate. This would ensure that the farmer in each year responds to the climate that she experiences. However, reliable annual weather data at district level for a long period of time is not available in India. The district level annual weather data for the period 1901–2002 at Climate Research Unit of the University of East Anglia, for instance is based on a small number of meteorological stations. Hence, climate data in the analysis correspond to the average weather over the period 1951–1980. However, we work under the assumption that the climate has not changed significantly over the study period and that the average weather over the 30-year periods is highly temporally correlated.[6]

Given the scope for the presence of unobserved variables that could confound with climate variables, it is possible to employ the district fixed-effects specification for efficient estimation. Such a specification would knockout the climate coefficients that are invariant over time. Deschenes and Greenstone (2007) in a recent study on US agriculture have used county fixed-effects specification and have assessed the value of weather shocks to the farmer as against the climate change impacts. The present study with its focus on climate change impacts attempts to address this issue by including state fixed effects. The year effects are captured through year fixed effects after the Hausman test rejected the null hypothesis, implying that the random effects model produces biased estimates. Further, since the units of analysis (that is, districts) differ significantly in size and agricultural activities, the measurement errors might also substantially differ across districts. Hence, we weigh the data for each unit of analysis by the total area under the 20 crops in order to adjust for heteroscedasticity.

Climate sensitivity and spatial autocorrelation

We can introduce spatial features into the Ricardian approach based on two arguments: (i) theory driven and (ii) data driven. In the theory-driven arguments, the focus is on interacting agents and social interactions (Anselin, 2002). This means that agents across space communicate with each other in order to learn about farm management practices and response strategies in order to handle climate and other risks. The assumption is that such interaction results in a spatially correlated dependent variable (and, sometimes, independent variables also). The resultant econometric specification then involves including a spatially lagged dependent variable as an additional independent variable.

In the data-driven specification, the focus is on accounting for the inefficiency being created by the possible presence of spatial correlation in the error terms of the linear regression models. Two immediate examples of these two types of specification can be seen in the climate change context. While Polsky (2004) introduces spatial econometric specification of the Ricardian model mainly to account for social interactions, Schlenker et al. (2006) bring in spatial features to arrive at *efficient* estimates of regression coefficients. Either way, the estimation procedure involves specifying the spatial weight matrix, which provides a structure to the assumed spatial relationships. The spatial models can be specified as follows:

$$\begin{aligned}&\text{Spatial-error model: } \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\eta},\\ &\text{where } \boldsymbol{\eta} = \boldsymbol{\rho}\mathbf{W}\boldsymbol{\eta} + \boldsymbol{\varepsilon},\end{aligned} \tag{3a}$$

$$\text{Spatial-lag model: } \mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{3b}$$

where, $\mathbf{y}$ is (*nx1*) vector of dependent variable observations, $\mathbf{X}$ is (*nxm*) matrix of observations on independent variables including the climate and other control variables, $\boldsymbol{\beta}$ is (*mx1*) vector of regression coefficients, $\boldsymbol{\eta}$ is (*nx1*) vector of spatially correlated error terms, $\boldsymbol{\rho}$ is (*1x1*) spatial autoregressive parameter, **W** is (nxn) spatial weights matrix and ε is ($nx1$) vector of random error terms. Note that **y** and **X** are, respectively, the left-hand and right-hand side variables specified in (1) above.

One of the crucial inputs that spatial analysis needs is the weight matrix **W.** We use three weight matrices—rook-based contiguity, queen-based contiguity and distance-based contiguity—in the present analysis. We generate these weight matrices for the Indian districts in GeoDa software.[7] We carry out spatial econometric analysis in GeoDa and STATA software for single cross-sections. However, since it is not feasible to estimate the spatial fixed-effects model in GeoDa (and also in STATA for computational limitations), we transfer the weight matrices via R-software to ASCII data format. We estimate the spatial panel models using MATLAB software[8] as it provides scope for reading sparse matrices.

Climate change projections for India and field studies

For the analysis, we use the climate change projections for India reported in Cline (2007). The climate change projections are the average of predictions of six general circulation models including HadCM3, CSIRO-Mk2, CGCM2, GFDL-R30, CCSR/NIES and ECHAM4/OPYC3. Table 1 shows the region-wise and season-wise temperature and rainfall changes for the period 2070–2099 with reference to the base period 1960–1990. From these regional projections, we assess the state-wise climate change predictions by comparing the latitude–longitude ranges of the regions with those of the states. In addition to this India-specific climate change scenario, we also assess the impacts for two illustrative uniform climate change scenarios (a +2°C temperature change along with a +7% precipitation change; and a +3.5°C temperature change along with a +14% precipitation change) that embrace the aggregate changes outlined in the fourth assessment report of IPCC (Solomon et al., 2007).

In an attempt to understand the scope and extent of information exchange between farmers, focus group meetings were held at around six villages each in Tamil Nadu and Andhra Pradesh.[9] The focus group meetings mainly explored the perceptions of the villagers about the climate change and their views on strategies helpful in ameliorating the climate change impacts. Among other things, special attention was paid to the channels through which information diffusion takes place.

Results and discussion

The results are reported in three subsections: in the first subsection, we present the estimates of the classic Ricardian approach, this is followed by a discussion on spatial diagnostics with different weight matrices; the last subsection reports the estimates of the panel data analysis under spatial-lag and spatial-error specifications and presents the

Table 1. *Projected changes in climate in India: 2070–2099.*

	January–March	April–June	July–September	October–December
Temperature change (°C)				
Northeast	4.95	4.11	2.88	4.05
Northwest	4.53	4.25	2.96	4.16
Southeast	4.16	3.21	2.53	3.29
Southwest	3.74	3.07	2.52	3.04
Precipitation change (%)				
Northeast	−9.3	20.3	21.0	7.5
Northwest	7.2	7.1	27.2	57.0
Southeast	−32.9	29.7	10.9	0.7
Southwest	22.3	32.3	8.8	8.5

Source: Cline (2007)

estimates of climate change impacts on Indian agriculture.

Climate response function—averaged regression

For purposes of comparison and carrying out spatial diagnostic tests, we average the data over the entire period of analysis to create a single cross-sectional data set. We use this single cross-sectional data set for estimating (1) using the weighted least squares approach, with area under cropland in each district serving as the weight. Table 2 reports the estimated regression coefficients.[10]

The estimated climate response function for the average data over the period 1966–1986 has several expected features with about 66% goodness-of-fit. A large number of climate variables are significant. Since soils tend to differ across districts, we include the soil variables mainly to control for the influence of cross-sectional variability of soil quality on the dependent variable. The other control variables include cultivators per hectare, bullocks per hectare and tractors per hectare. Both cultivators and bullocks have a mixed expected influence on the farm-level net revenue. On the one hand, the higher values of these variables reduce the cost to the farmer, but on the other hand, high values also represent labour intensive farming and hence a low technological base. Tractors per hectare clearly have a high significant positive influence on farm-level net revenue. Literacy and population density have a positive effect as expected. The percentage of land under irrigation clearly increases farm-level net revenue. Some studies have argued against the use of irrigation as one of the explanatory variables due to the potential endogeneity problem and have suggested instead the use of area under high-yielding variety cultivation. However, since most of the irrigated land also cultivates high-yielding variety crops, these two variables could be largely collinear.

Most of the climate variables are significant and the estimated response function appears to be nonlinear, in line with available evidence in the literature. Magnitudes of the temperature coefficients are higher than those of the precipitation coefficients, indicating relatively higher sensitivity crop growth

Table 2. *Climate response function—averaged regression.*

Variable	Coefficient	t-statistic
January temperature	−435.34	−1.84
April temperature	−593.01	−2.31
July temperature	−946.30	−2.05
October temperature	2170.91	3.68
January precipitation	31.67	1.11
April precipitation	−14.19	−1.62
July precipitation	−2.07	−1.06
October precipitation	28.62	2.86
January temperature sq.	−46.11	−1.22
April temperature sq.	127.10	1.89
July temperature sq.	−102.44	−0.75
October temperature sq.	−264.03	−3.39
January precipitation sq.	−2.56	−2.85
April precipitation sq.	0.17	2.26
July precipitation sq.	0.004	1.00
October precipitation sq.	0.03	0.33
January temperature × precipitation	−32.64	−2.99
April temperature × precipitation	15.19	4.34
July temperature × precipitation	−1.21	−0.94
October temperature × precipitation	−2.60	−0.61
Soil type 1	296.94	0.96
Soil type 2	1449.99	3.59
Soil type 3	−907.00	−1.69
Soil type 4	55.70	0.13
Top-soil depth class 1	−535.40	−0.66
Top-soil depth class 2	137.34	0.16
Cultivators per hectare	1125.11	1.63
Bullocks per hectare	−325.89	−0.42
Tractors per hectare	286077.50	3.30
Literacy	1577.35	0.85
Population density	184.36	1.48
Percentage of irrigated land	3786.24	3.25
Altitude	−0.98	−1.00
Intercept	4717.93	3.62
Number of observations	271	
Adjusted R^2	0.668	

to temperature changes (Lobell and Burke, 2008). The temperature coefficients are all negative in January (winter), April (spring) and July (summer) but positive in October (autumn). While higher temperatures during the hot spring and summer days would adversely influence crop growth, warmer autumns could lead to an enhanced growing season. Higher temperature during winter could favourably influence pest growth and hence could have an adverse impact on crop growth. Higher precipitation as expected is beneficial in the winter and autumn seasons but harmful during spring and summer probably due to reduced solar radiation.

For purposes of comparison with the spatial models, we carry out a pooled regression analysis covering all the years of the study period with exactly similar specification as the averaged regression discussed here. In addition to all the variables discussed above, we include the year fixed effects in the panel data analysis. All the coefficients retained the sign and magnitude in the pooled regression and have improved statistical significance. Almost all the climate coefficients were statistically significant in the pooled regression (we report these results later in Table 4 along with spatial panel data analyses results).

As discussed above, a valid criticism of the Ricardian approach is unobserved cross-sectional variables confounding with climate variables. And including district fixed effects in the pooled data analysis is not feasible given the non-varying nature of some of the independent variables, including the climate variables, over the years. In an attempt to improve the model specification, we added regional fixed effects to (1) in the form of state dummies. Almost 70% of the climate variables remained significant in the model with state dummies, confirming that regional fixed effects have not nullified the influence of climate on farm-level net revenue. Barring a few exceptions, the direction of influence also remained similar between models without and with regional fixed effects. The magnitude of individual coefficients however has changed as was to be expected. But, we did not include the regional dummies for the rest of the analysis.

Diagnostics for spatial dependence

We analyze the spatial clustering of the dependent variable (that is, net revenue per hectare) and the residual of the ordinary least squares, regression by constructing Moran scatter plots for several time points in the period 1966–1986. The scatter plot is a graph of $\mathbf{Wy}$ versus $\mathbf{y}$, where $\mathbf{W}$ is a row-standardized spatial weight matrix and $\mathbf{y}$ = [(variable value − mean of variable)/standard deviation of variable]. We use a rook-contiguity-based weight matrix for constructing the Moran scatter plots. The slope of the best-fit line through the points on the scatter plot provides a measure of Moran's I spatial autocorrelation statistic for the data set. The Moran's I statistic for the dependent variable as well as the error for 1970, 1975, 1980 and 1985 are, respectively, 0.223, 0.353, 0.395, 0.431 and 0.158, 0.136, 0.176, 0.105 (all statistically significant with p value of 0.000). The positive value of Moran's I statistic indicates clustering of values in the upper right quadrant and lower left quadrant of Moran's scatter plot and hence represent positive spatial autocorrelation.

The indication of significant spatial clustering given by the spatial autocorrelation statistic represents only the first step in the analysis of spatial data. We carry out spatial diagnostic tests on the averaged regression reported in the previous section to statistically assess the extent of spatial dependence in the data and to identify the appropriate correction for removing the spatial dependence in the data. Table 3 reports various test statistics under different weight matrix specifications.

The first row in Table 3 shows the Moran I statistic of the error along with the associated probability. It shows the statistic to be highly significant indicating the problem of spatial dependence in the data. The value of Moran I statistic is close to 0.2 across the different weight matrix specifications indicating that alternative weight matrices may not have a significant influence on the analysis.

Following Anselin (2005), we use the Lagrange multiplier test to determine which spatial model should be used for spatial correction (spatial lag or spatial error). The sequence of the search is as follows: if both Lagrange multiplier (lag and error) statistics are significant, then we consider the robust versions of these tests to be significant and we choose the model specification with the higher significance for the spatial analysis. In all cases reported in Table 3, the Lagrange multiplier (lag and error) statistics are highly significant, necessitating the need for examining the robust Lagrange multiplier test statistic. In rook-contiguity and queen-contiguity-based weight matrix specifications, the robust Lagrange multiplier statistics for both lag and error are significant, with the latter highly significant compared to the former. In the

Table 3. *Spatial diagnostics—averaged regression.*

Diagnostic parameter	Weight matrix		
	Rook-contiguity	Queen-contiguity	Distance-based (50 km)
Moran I (error)	0.19917 (0.000)	0.19394 (0.000)	0.20392 (0.000)
LM (lag)	14.94 (0.000)	14.41 (0.000)	7.33 (0.006)
Robust LM (lag)	3.56 (0.059)	3.41 (0.065)	0.81 (0.267)
LM (error)	26.53 (0.000)	26.05 (0.000)	14.55 (0.000)
Robust LM (error)	15.15 (0.000)	15.05 (0.000)	8.03 (0.004)

Note: Values in the parentheses are *p* values, LM—Lagrange multiplier

case of distance-based weight matrix specification, however, the robust Lagrange multiplier tests suggest the spatial-error model as the preferred model for spatial correction.

Effect of spatial autocorrelation on climate sensitivity

The evidence presented above based on the averaged regression makes it clear that: (a) the choice of the weight matrix may not have a significant influence on the analysis and (b) the choice of the model for spatial correction—namely, spatial lag and spatial error—is not obvious, with the robust Lagrange multiplier test statistic remaining significant under lag as well as error specifications. Hence, we use both these models for spatial correction and re-estimate (1) with the modifications specified in (3a) and (3b) using the panel data over the period 1966–1986. We base all the estimates on fixed (year) effects specification in the pooled data and the observations are weighted by the total area under all the crops considered in the analysis. Thus, we attempt two kinds of heteroscedasticity corrections in the spatial analysis: the first is through the crop area in each district in order to account for differences in the size of the districts and hence the difference in the measurement error; and the second is through the weight matrix in order to account for spatial dependence in the data. We use the rook-contiguity-based weight matrix to estimate the spatial models.

Table 4 shows the climate response functions estimated with and without consideration of spatial autocorrelation. Though the adjusted R^2 value is higher under both the spatial models, it is what is known as the pseudo R^2 and hence not exactly comparable with that in ordinary least squares estimation (Elhorst, 2003). Most of the climate coefficients in both the spatial-lag and spatial-error models are significant and have a similar influence as the base model without the spatial correction. Barring a few exceptions, the climate coefficients in the models that account for spatial autocorrelation (either through spatial-lag or spatial-error models) are uniformly lower than that which ignores the presence of spatial autocorrelation. This implies that the explanatory power of the climate variables that we attributed to their within district value in the base model was partly due to the influence of neighbouring districts.

With regard to the choice between the two spatial models, the diagnostic tests were inconclusive as discussed in the previous section. The coefficient of the spatially lagged farm-level net revenue in the spatial-lag model and the coefficient of spatially correlated errors in the spatial-error model are both positive and highly significant. The model performance parameters, the higher adjusted R^2 value (0.72 versus 0.65) and the higher log-likelihood value (-127406 versus -127861), indicate that the spatial-error model is preferred over the spatial-lag model.

In order to gain insight into the influence of various climate change scenarios on Indian agriculture, we assess the impacts based on the estimated climate response functions. We consider two climate scenarios: (a) one illustrative scenario with a +2°C uniform change in temperature and a +7% uniform change in precipitation (b) one India-specific scenario with the expected regional changes in temperature

Table 4. *Climate response function—pooled regression with spatial correction.*

Variable	Without spatial autocorrelation		With spatial autocorrelation			
			Spatial-lag model		Spatial-error model	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Climate variables						
January temperature	−443.3	−6.5	−394.8	−5.6	−395.3	−5.1
April temperature	−695.5	−9.6	−537.1	−7.5	−668.5	−8.3
July temperature	−817.9	−6.1	−575.3	−4.3	−809.3	−5.4
October temperature	2160.4	12.5	1833.0	10.5	1709.0	9.2
January precipitation	38.5	4.6	13.6	1.6	−7.3	−0.8
April precipitation	−17.2	−6.8	−14.6	−5.5	−7.8	−2.9
July precipitation	−2.2	−3.9	−1.3	−2.2	−2.5	−4.3
October precipitation	29.5	10.1	20.8	7.1	18.4	5.9
January temperature sq.	−43.8	−3.9	−24.1	−2.1	−11.4	−1.0
April temperature sq.	118.4	6.2	101.9	5.2	139.0	6.5
July temperature sq.	−96.9	−2.5	−25.6	−0.6	117.7	2.7
October temperature sq.	−264.0	−11.6	−234.0	−10.1	−236.3	−9.7
January precipitation sq.	−2.8	−10.6	−2.6	−9.5	−1.9	−6.5
April precipitation sq.	0.2	8.0	0.2	6.9	0.097	4.8
July precipitation sq.	0.004	3.4	0.005	4.5	0.002	2.1
October precipitation sq.	0.028	1.2	0.1	3.8	0.057	2.3
January temperature × precipitation	−36.3	−11.4	−38.5	−11.7	−26.8	−7.2
April temperature × precipitation	15.8	15.7	15.2	14.7	10.3	10.5
July temperature × precipitation	−1.5	−4.0	−0.7	−1.8	−0.4	−0.9
October temperature × precipitation	−2.9	−2.3	−4.1	−3.2	1.8	1.3
Control variables						
Cultivators/ha	382.1	2.3	163.1	1.0	758.5	5.0
Bullocks/ha	91.2	0.4	558.4	2.6	1105.6	5.5
Tractors/ha	153798	9.6	63282	4.1	67539	4.3
Literacy	2780.0	5.4	4039.0	8.5	3160.2	6.5
Population density	128.8	3.9	174.5	4.8	182.0	4.7
Irrigation %	2643.9	9.3	2648.4	9.4	3538.1	13.0
Spatial lag/Spatial autocorrelation			0.0649	4.3	0.57	4.2
Number of observations	5691		5691		5691	
Adjusted R^2	0.5464		0.6517		0.7233	

Note: The model specification is same as equation (1); soil variables are not reported to save space

and precipitation as reported in Table 1. We measure the climate change induced impacts through changes in the net revenue triggered by the changes in the climate variables. We estimate the impacts for each year at the individual district level, which we then aggregate to derive the national level impacts. We report the average impacts over all the years in Table 5. The table reports the all India level impacts estimated in each time period as a percentage of the 1990 all India net revenue expressed in 1999–2000 prices. We consider the 1990 net revenue mainly to accommodate a comparison with previous results reported in the literature. We interpret the impacts as a change in 1990 net revenue if future climate changes were to be imposed on the 1990 economy and are annual impacts. We estimate that the overall impacts (for the same climate change scenario) using climate coefficients obtained from the model that accounts for spatial autocorrelation (either through spatial-lag or through spatial-error specification) are significantly lower than those obtained from the model that ignores the spatial effects.

Table 5. *Climate change impacts—without and with spatial autocorrelation.*

Scenario ($\Delta T/\Delta P$)	Without spatial autocorrelation		With spatial autocorrelation: Spatial lag model		With spatial autocorrelation: Spatial error model	
	Impacts	% of 1990 net revenue	Impacts	% of 1990 net revenue	Impacts	% of 1990 net revenue
+2°C/7%	−81.2	−9.17	14.2	1.6	−22.9	−2.6
India specific CC scenario	−195.1	−22.1	43.4	4.9	−2.1	−0.23

Note: Impacts are in billion rupees, 1999–2000 prices. Net revenue in India in 1990 is Rs. 885 billion (1999–2000 prices)

This is because the aggregate net revenue estimated for changed climatic conditions using the spatial models is higher than that estimated using model that does not account for spatial effects.

Since the aggregate impacts mask significant regional differences, Figures 1 and 2 compare the distribution of climate change impacts at the state and district levels between the models that account for spatial autocorrelation and those that do not. For these figures, we use the India-specific climate change scenario that incorporates non-uniform changes in temperature and precipitation across regions. The results show that climate change is likely to adversely affect agriculture in almost all the regions in India with the exception of the eastern states of Bihar and West Bengal along with the inland region of Karnataka. Severe impacts are borne by the high-value agricultural regions of Haryana, Punjab and Uttar Pradesh along with the dry regions of Gujarat and Rajasthan. Coastal states like Andhra Pradesh and Tamil Nadu also lose out under changed climatic conditions. Between the models that do not incorporate spatial correction and the models that do, we predict significant changes in Andhra Pradesh, Tamil Nadu, Rajasthan, Madhya Pradesh and to some extent in Uttar Pradesh. This means that in the case of these states, the model without spatial correction overestimated the climate change impacts.

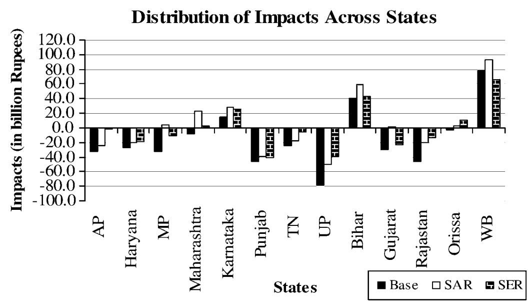

Figure 1. *State-wise distribution of climate change impacts: without and with spatial correction.*
Note: Base—model without spatial correction, AP, Andhra Pradesh, MP, Madhya Pradesh, SAR—spatial-lag model, SER—spatial-error model, TN, Tamil Nadu and UP, Uttar Pradesh.

Conclusions and policy recommendations

This paper contributes to existing knowledge on the impacts of climate change on Indian agriculture by accounting for spatial issues in a Ricardian framework. Using ~20 years of district level agricultural data coupled with climate and soil data, the analysis employs spatial panel data models to explore these issues. Besides estimating the climate response function for Indian agriculture, the paper estimates the expected impacts due to climate change on Indian agriculture.

The evidence presented in this paper suggests that (a) accounting for spatial autocorrelation is important due to the presence of significant spatial clustering of the data and (b) the climate change impacts are significantly lower after incorporating spatial correction either through spatial-lag or through spatial-error model specifications. The choice between spatial-lag and spatial-error model specifications for spatial correction is largely inconclusive. However, purely from a model performance perspective, the spatial-error model has a slight edge over the spatial-lag model.

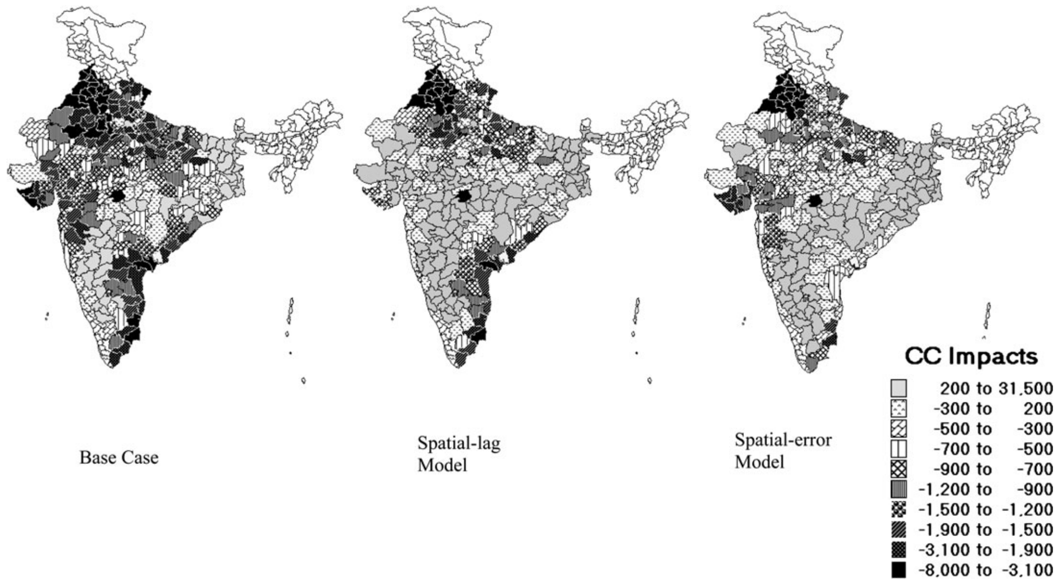

Figure 2. *Distribution of climate change impacts across districts—without and with spatial correction.*
Note: Base—model without spatial correction.

The impacts of climate change on agricultural net revenue estimated in this paper are lower than the range of results obtained from other climate change agricultural impact studies in India. Under an illustrative climate change scenario of +2°C temperature change and +7% precipitation change, the results from this study estimate an annual decline of 3% in farm-level net revenue. On the other hand, for a similar climate change scenario but without accounting for the spatial autocorrelation, Kumar and Parikh (2001b) and Sanghi and Mendelsohn (2008) estimate, respectively, 8.4% and 12% decline annually in farm-level net revenue in India. The impacts on the gross domestic product estimated by Kumar and Parikh (2001a) are not strictly comparable with those reported in the above studies due to the partial equilibrium approach adopted in the Ricardian framework. However, yield losses estimated by Kumar and Parikh (2001a) and others reported in Mall et al. (2006) are relatively higher than the losses in net revenue estimated by the Ricardian studies.

We also estimate the impacts due to an India-specific climate change scenario along with the regional distribution of impacts. With the exception of the eastern states of Bihar and West Bengal and the inland region of Karnataka, in all other regions of India climate change is likely to have an adverse impact on agriculture. These findings could reinforce the 'look towards east' policy of Indian government. Further this study findings show that in the case of Andhra Pradesh, Tamil Nadu, Rajasthan, Madhya Pradesh and, to some extent, Uttar Pradesh, incorporating the spatial effects results in a lowering of the climate change impacts on agriculture.

The assessment of climate change impacts on Indian agriculture through a careful consideration of spatial issues in the Ricardian framework that this study has carried out would be useful in providing a more accurate picture of the potential impacts of climate change on Indian agriculture. However, from a policy perspective, it would be helpful to identify factors that contribute to the observed spatial correlation of variables across districts. Such knowledge would be useful in designing policies that contribute to enhancing the facilitating factors. While the factors contributing towards the spatial effects are unclear, this study explored the possible role played by a strong flow of information among farmers in contributing to better adaptation and thereby lower the impact of climate change on agriculture. The field level observations discussed here are based on limited number of focus group discussions and are only indicative. More detailed studies are needed to further substantiate these findings.

Focus group interviews from the field indicate that the main sources of information to farmers are the more affluent farmers in the neighbourhood, fertilizer and pesticide dealers, seed providers and the better informed family members. Contrary to the general belief that agricultural extension centres operate as the primary source of information, the evidence from the field suggests that, in reality, farmers could benefit little from these government outfits. While market sources seem to have the appropriate self-regulated checks against the provision of wrong information, it is important to ensure that incorrect information does not reach the farmers even inadvertently.

The field studies also reveal that policy makers should explore and experiment with new sources of information diffusion. Given the fragmented nature of Indian agricultural lands, the large-scale participation of the corporate sector in providing agricultural extension services would be difficult, thereby necessitating the exploration of other options. Among other options, the farmers favoured in particular the participation of agricultural cooperatives, non-governmental organizations (NGOs), and dealers of inputs and fertilizers in information diffusion. In this context, it might be worthwhile to carefully study other country experiences in order to identify the routes through which the State can provide agricultural extension services to the farmers in India. For instance, in Ecuador, the agricultural extension workers operate in tandem with the farmers through share cropping in order to ensure proper information diffusion. On the other hand, Chile finances the costs of private sector firms that transfer technology know-how and information on new agricultural practices to small-scale farmers. Similarly, role of information and communication technology in agricultural knowledge diffusion should also be carefully studied.

The Ricardian approach we used in this study deals largely with private adaptation measures undertaken by farmers for whom not adapting (that is through changes in crop-mix and crop management practices) would be suboptimal. However, climate change also requires large-scale public adaptation alongside the afore-mentioned private adaptation practices. Future research in this field could focus on the nature of such adaptation as well as assessment of cost-effective adaptation strategies in order to ameliorate the adverse impacts of climate change on Indian agriculture. For mainstreaming the climate change concerns especially in developing countries like India, such strategies should seamlessly merge with the overall development agenda.

Endnotes

[1] A few studies have used a third approach based on the agro-ecological zones methodology of the Food and Agricultural Organization (Fischer et al., 2002).

[2] Higher carbon dioxide concentrations in the atmosphere under the climate change conditions could act like aerial fertilizers and boost crop growth.

[3] Soil types considered include laterite, red and yellow, shallow black, medium black, deep black, mixed red and black, coastal alluvium, deltaic alluvium, calcerous, grey brown, desert, tarai, black, saline and alkaline, alluvial river, skeletal, saline and deltaic, red and red and greyely soils.

[4] We do not include the cost of household/non-hired labour in the net revenue estimation as appropriate wage rate is difficult to get. Cultivators—self-employed males who list their primary job classification as farming—are included as proxy for household/non-hired labour.

[5] This relatively older time period was chosen to enable comparability of the basic findings from this study with those available in the literature (namely, Kumar and Parikh, 2001b; Sanghi and Mendelsohn, 2008) that do not account for spatial effects.

[6] We acknowledge that some studies (see Dash et al., 2009; Naidu et al., 2009; Niyogi et al., 2010) report that climate, especially rainfall, has changed in the recent years over India. However, Sanghi and Mendelsohn (2008) in their analysis use climate data corresponding to the period 1930–1960 and report almost similar results as in this study. This is seen as justification for the above claim that the climate has remained stable over the study period.

[7] The spatial econometric software developed by Prof. Luc Anselin of the University of Illinois (version 0.9.5).

[8] J. Paul Elhorst (www.spatial-econometrics.com) has written the MATLAB codes for spatial panel analysis.

[9] The field studies were carried out during the months of March–April 2008 with the help of local NGOs. In Tamil Nadu, the villages covered included Manampathy, Thevoor, Kumaramangalam, Echur, Arungunram and Thirunilai. In Andhra Pradesh, Kothapatnam, Nidavanur, Kuchipudi, Nilayeepalem and Chinagangam villages were covered for the focus group discussions.

[10] In order to keep the analysis focused on climate variables, we do not report the influence of weather variability on climate sensitivity. Kumar (2003) analyses the robustness of climate coefficients in the presence of weather variability and argues that climate continues to play important role even in the presence of weather variability in the model specification.

Acknowledgements

The author would like to acknowledge gratefully the financial support received from South Asian Network for Development and Environmental Economics. The author is grateful to Jeff Vincent, Priya Shyamsundar, Madhu Verma, Jean Marie Baland, Brinda Viswanathan, Jaya Krishnakumar, Shreekant Gupta, Mani Nepal and Pranab Mukhopadhaya for providing constructive feedback during the course of the work. This paper has been presented at the *IV Congress of the Latin American and Caribbean Association of Environmental and Natural Resource Economics*, 19–21 March 2009, in Heredia. The author would also like to acknowledge the valuable comments provided by two anonymous reviewers on the earlier drafts of this paper.

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